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Optimization of process parameters through fuzzy logic and genetic algorithm – A case study in a process industry

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ABSTRACT

The simultaneous generation of steam and power, which is commonly referred to as cogeneration, has been adopted by many sugar mills in India to overcome the power shortage. It becomes an increasingly important source of income for sugar factories. The problems faced by the sugar mill industry arise mainly due to failures of either the complete system or some specific components during the cogeneration process. This paper presents the failure analysis of the boiler during the cogeneration process and provides solution to overcome these failures. The failures frequently occur in the screw conveyor and in the drum feeder of fuel feeding system and the grate of the boiler. In this research work, the statistical tools viz., Failure Mode and Effect Analysis (FMEA) and the Taguchi method have been applied to investigate and alleviate these failures. Since conventional FMEA has some limitations and Taguchi method does not give better solution, fuzzy FMEA has been employed to overcome the limitations and genetic algorithm technique has been applied to obtain failure – free system during the cogeneration process.

1. Introduction

The growth of Indian economy is constrained by shortage of power, which is one of the significant constraints. Therefore simultaneous generation of steam and power, commonly referred to as cogeneration, has been adopted in many of the sugar industries [1]. A steam generating boiler is one of the essential prime movers used in cogeneration process and nevertheless boiler failures are one of the major causes for unexpected shutdown of plant, leading to a great loss of production [2]. This research work has been carried out in one of the leading sugar industries located in Tamil Nadu as a case study. The boiler used in the sugar mill is a high pressure and water tube boiler type which is vertical and top supported. The working pressure, generating capacity and steam temperature of this boiler are 66 kg/cm^2, 75 tonnes/hour (T/h), and 485 °C respectively. The main components used in cogeneration boiler are fuel feeding system, furnace (grate), super heater, attemperator, economizer, air pre-heater, Forced Draught (FD) fan, Induced Draught (ID) fan, dust collector, boiler feed water pumps and some auxiliary equipments [3].

The fuel feeding system consists of a storage bunker (silo), drum feeder and a screw conveyor. After extracting sugar, the remaining fibrous residue, which is called bagasse, is used as fuel in the boiler, otherwise, it would be conveyed to the storage facilities. In order to compensate the shortage of bagasse, other fuels such as palm boom, wood chips and cane trash are looked for. This boiler is designed to burn bagasse (B), palm boom (PB), cane trash (C) or a mixture thereof [4,5]. The fuel is fed to the vertical column of the storage bunker (silo) from the belt conveyor. The combination of drum feeder and screw conveyor combination is intended to feed desired quantities of bagasse to the furnace.

The drum feeder extracts bagasse from storage bunker and the quantity extracted is proportional to the speed of rotation of the drum. The extracted bagasse is fed to the screw conveyor which transports the same longitudinally and further into the chute which connects the conveyor and pneumatic distributor. In fact, four such assemblies are available per boiler in the system. Fuel is burnt in suspension as well as during the forward travelling grate surface. Later the ash is continuously discharged over the front end of the grate into the ash handing system. The formed flue gas is passed around the water tubes and further through the economizer, air pre-heater, super heater, dust collector and finally to the air precipitator. Thus the steam generated in the boiler is utilized for power generation. In the above-mentioned boiler, failures are frequently

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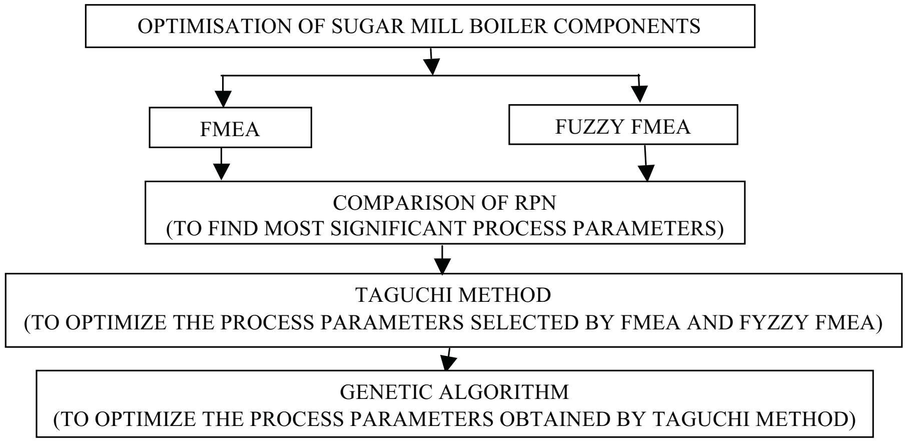

Fig. 1. Methodology of research plan.

Table 1
Traditional FMEA scales for RPN.

Occurrence (*O*) Severity (*S*) Detection (*D*)	Scale	Occurrence rate	Detection probability (%)
Remote	1	<1:20,000	86–100
Low	2/3	1:20,000/1:10,000	76–85/66–75
Moderate	4/5/6	1:2000/1:1000/1:200	56–65/46–55/36–45
High	7/8	1:100/1:20	26–35/13–25
Very high	9/10	1:10/1:2	6–15/0–5

occurring in the screw conveyor, drum feeder and grate. The work plan for this research work is shown in Fig. 1.

In this research work as shown in Fig. 1, a sugar mill boiler has been selected. The problem identified in the above-mentioned industry is minimizing the failures of the system by optimizing the process parameters. The failures have occurred in the drum feeder, screw conveyor and the grate during cogeneration process. In the first stage, RPN values have been ascertained using FMEA and fuzzy FMEA. The most significant parameters that cause the failures are identified from the comparison of conventional RPN and fuzzy RPN values. Further, these significant parameters are optimized by Taguchi method and subsequently by genetic algorithm in order to obtain failure free system.

Failure Mode and Effects Analysis (FMEA) is a very powerful tool for evaluating and enhancing system reliability that is used in a wide variety of industries including aerospace, automotive, medical, mining, offshore and power generation. FMEA is a widely used engineering tool for defining, identifying and eliminating known as well as potential failures, problems, errors and so on from system, design, process, and/or service before they reach the customer [6,7]. A system, design, process, or service may usually have multiple failure modes or causes and effects. In this situation, each failure mode or cause needs to be assessed and prioritized in terms of their risks so that highly risky (or most dangerous) failure modes can be corrected with top priority. The traditional FMEA determines the risk priorities of failure modes through the risk priority number (RPN), which is the product of the occurrence (*O*), severity (*S*) and detection (*D*) of a failure. That is $RPN = O \times S \times D$, where *S* represents the severity of the failure, *O* represents the probability of the failure occurrence, and *D* represents the probability of the failure being detected [8]. The severity, occurrence and detection factors are individually rated using the 10-point scale described in Table 1. The minimum value ("no risk") is rated with 1. Failure modes with higher RPN values are considered to be more important and are given higher priorities than those with lower RPN values [9]. However, it suffers from several shortcomings. It has been pointed out that the same RPN can be obtained from different combinations of severity, occurrence, and detection. Although the same RPN is obtained, the risk can be different and the relative importance of three risk factors (*O*, *S* and *D*) is not taken into account. In other words, the three risk factors are given of equal importance, but this may not be the case in practice. The three risk factors are difficult to evaluate precisely. Typically, division is made with the usage of linguistic terms such as low, higher very high. In order to overcome the above shortcomings, fuzzy logic is applied into the conventional FMEA in the present work [10,11].

2. Methodology of fuzzy inference system

Fuzzy logic system is one of the various names for the systems which have relationship with fuzzy concepts like fuzzy sets, linguistic variables, etc. The most popular fuzzy logic systems in the literature may be classified into three types: pure fuzzy logic systems, Takagi and Sugeno's fuzzy system, and fuzzy logic systems with fuzzifier and defuzzifier. The three inputs *S*, *O* and *D* are fuzzified and evaluated in a fuzzy inference engine built on a consistent base of IF–THEN rules. The fuzzy output is defuzzified to get the crisp value of the RPN which will be further used for a more accurate ranking of the potential risks [12,13]. Fuzzy inference system (FIS) is based on IF–THEN rules which can connect multiple input variables to output variable. FIS could be utilized as a forecasting model when input/output data have some uncertainties. Detection assessment methodology is based on FIS and therefore it provides a flexible way for recognizing their effective factors and modelling. Input variables are fuzzified by the fuzzy membership functions and they are imported to fuzzy inference engine. In a fuzzy inference engine, experts' knowledge about failure detection is converted into If–Then rules. Fuzzy inputs are assessed by fuzzy inference engine and finally output or detection score is defuzzified [14].

2.1. Application of the proposed approach to process industry

Taguchi–genetic algorithm approach has been applied to optimize the welding process parameters of friction welding of tube-to-tube plate using an external tool (FWTPET) [15]. The practical significance of applying GA to FWTPET process has been validated by means of computing the deviation between predicted and experimentally obtained welding process parameters. This process yields high quality and defect-free weld joints with enhanced mechanical and metallurgical properties with lesser energy consumption [15]. Although the evolutionary algorithms offer significant advantages over the traditional techniques, they may have premature convergence towards a local minimum. In

order to overcome the weaknesses of evolutionary algorithms and to avoid premature convergence towards a local minimum, evolutionary optimization techniques have been hybridized and commonly used in the optimization of manufacturing and design optimization problems [16]. Fuzzy-genetic algorithm approach has been applied to improve the quality of the drawing in the automatic orthogonal graph drawing and it has been proved that the proposed approach generates the solutions with superior characteristics relatively the solutions obtained with applying the classical approach [17]. While reviewing the GA technique, Oscar Castillo et al. [18] considered the application of genetic algorithms, particle swarm optimization and ant colony optimization in the design of optimal type-2 fuzzy controllers. They also mentioned alternative approaches to design type-2 fuzzy controllers without optimization techniques. Comparison of the different optimization methods for the case of designing type-2 fuzzy controllers has been provided. Particle swam optimization (PSO) and genetic algorithms (GAs) are combined for optimization using fuzzy logic to integrate the results of both methods and for parameters tuning. The new optimization method gives improved results than PSO and GA [19]. Fuzzy and genetic algorithm techniques were used in assembly line balancing problem. In this work, fuzzy goal programming has been used to address uncertainties in the conventional criteria and an appropriate genetic algorithm has been developed to deal with the model and results show that well balanced task allocation can be obtained through the proposed model [20]. Finite element method and genetic algorithm approach were applied to optimize the electric discharge machining parameters. It has been found that the proposed approach gives expected optimum performance of the EDM process [21]. The genetic algorithm technique has been used to mechanize the optimal determination of fuzzy logic controller parameters based on an efficient cost function that comprises undershoot, overshoot, rise time, settling time, steady state error and stability. Simulation results show that the proposed strategy performances are desirable in terms of the time response characteristics for both phugoid mode and short period mode, the robustness, and the adaptation of itself with respect to the large commands [22].

Generally in sugar mill boiler, in the first instant, conventional FMEA using RPN ranking is applied as a first step to ascertain the failure modes. Mathematically, RPN = $O \times S \times D$. FMEA is carried out by a cross-functional team of experts from various departments [23]. By using experts' knowledge, the values of O, S and D are assigned to various failure modes from Table 1. The RPN values of the identified process parameters causing failures for boiler are shown in Table 2. If the RPN value of any parameter is more than 100, that parameter will be considered as most critical parameters.

2.2. Fuzzy membership function

The membership function represents the degree of memberships of input and output linguistic variables. The fuzzy membership functions for the linguistic terms of the severity,

Table 2
Conventional FMEA for boiler.

Sl. No.	Process function	Potential failure modes (process defects)	Potential causes of failure	S	O	D	RPN
1	Co generation process	Screw conveyor failure	*Fuel type	6	6	7	252
			Size of fuel	3	4	5	60
			Foreign material	2	3	3	18
			*Fuel moisture	7	8	6	336
			Improper maintenance of eddy current	2	4	3	24
			Gears not properly connected in the drum	3	3	4	36
			*Drum speed	6	8	8	384
			Motor damaged	3	4	4	48
			*Air flow	7	7	8	392
			Improper maintenance	2	2	4	16
			Mal function	4	4	2	32
			Fatigue	4	2	1	8
2		Drum failure	*Fuel type	6	7	7	294
			Size of fuel	5	3	3	45
			Foreign material	3	3	3	27
			*Fuel moisture	7	7	8	392
			Improper maintenance	3	4	3	36
			Mal function	2	4	5	40
			Fatigue	2	2	2	8
			*Fuel level	7	7	7	343
			Door not properly closed	3	6	3	54
			*Motor load (current)	8	8	6	384
			Relay contact	2	3	7	42
			Rotation improper	4	2	2	16
			Oil level in gear box	3	3	5	45
3		Grate failure	*Furnace-temperature	7	6	6	252
			Fuel heap	2	3	5	30
			Air flow	3	2	4	24
			*Fuel type	6	6	8	288
			Size of fuel	3	2	2	12
			Foreign material	4	3	4	48
			Fuel moisture	3	4	6	72
			*Hydraulic drive-speed	6	5	8	240
			*Oil pressure	7	7	5	245
			Oil seal damaged	5	3	3	45
			Oil level	4	4	4	64
			Improper lubrication	2	3	1	6
			Improper maintenance	3	3	5	45
			Mal function	5	4	3	60
			Fatigue	1	5	3	15

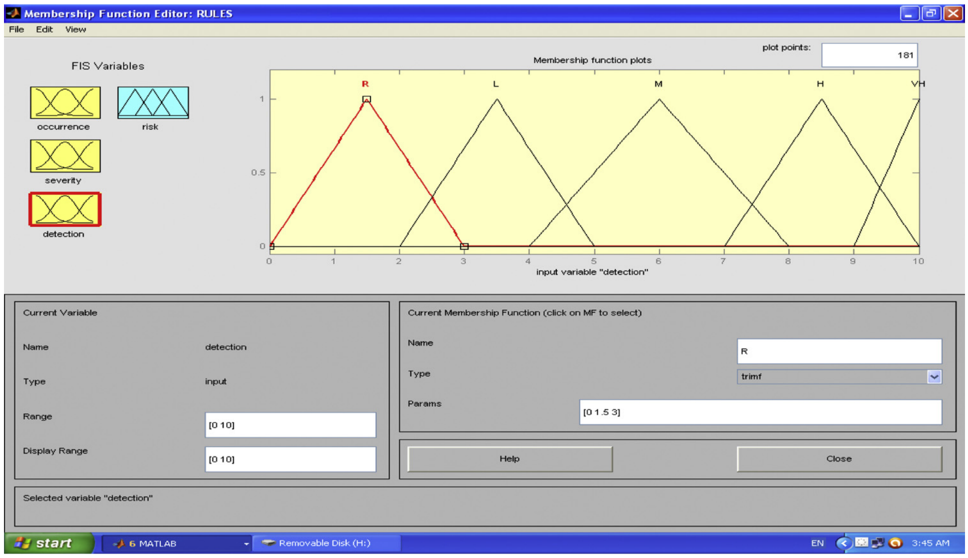

Fig. 2. Membership function for occurrence (identical for severity and detection).

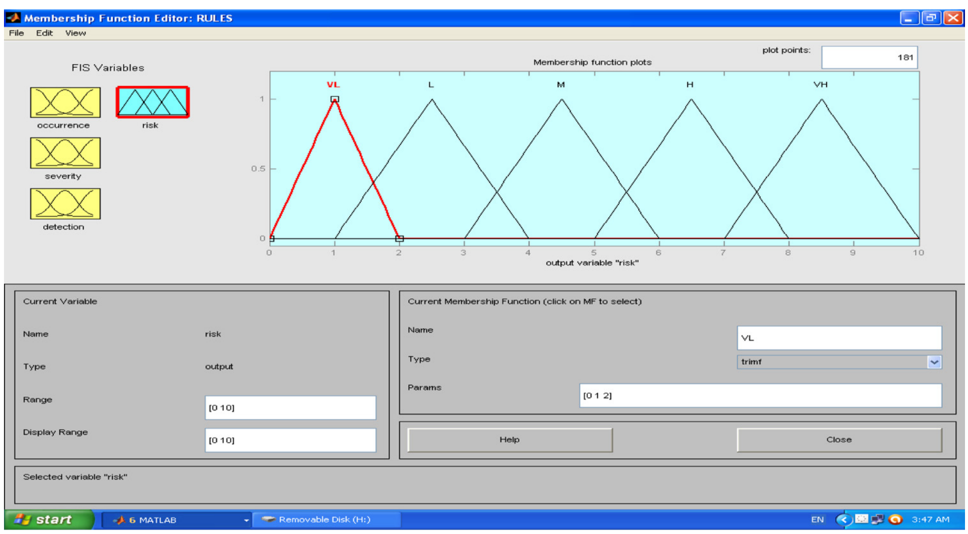

Fig. 3. Membership function for the risk for sugar mill boiler.

occurrence and detection are described in Table 3. The most common ones are triangular, trapezoidal and Gaussian type membership functions. The three inputs, severity, occurrence and detect are described by remote, low, moderate, high and very high as linguistic terms. The output, risk is described by very low, low, moderate, high and very high as linguistic terms [24,25]. In this paper, the triangular membership functions are used for assessments. Fig. 2 represents input variable (severity, occurrence and detection) membership functions. The output variable (risk) membership function is represented in Fig. 3. These membership functions will be used in fuzzy FMEA for determining the potential constructability problems.

2.3. Fuzzy rule base

The membership function derived from the expert is used to generate the fuzzy rule base. Since there are three factors, severity, occurrence and detection and each factor are described by five linguistic terms, the total number of rules is 125. Some of these rules can be combined to reduce the number of rules of the fuzzy rule base. The total number of rules, equal to 125, in the fuzzy rule base, is reduced to 24 for boiler. The rules, which are written in MATLAB software are given below:

1. IF Occurrence is M and Severity is M and Detection is H, THEN Risk is H.
2. IF Occurrence is L and Severity is M and Detection is M, THEN Risk is L.
3. IF Occurrence is L and Severity is L and Detection is M, THEN Risk is VL.
4. IF Occurrence is H and Severity is H and Detection is M, THEN Risk is VH.
5. IF Occurrence is L and Severity is M and Detection is L, THEN Risk is VL.
6. IF Occurrence is L and Severity is L and Detection is M, THEN Risk is L.
7. IF Occurrence is M and Severity is H and Detection is H, THEN Risk is VH.
8. IF Occurrence is H and Severity is H and Detection is H, THEN Risk is VH.
9. IF Occurrence is M and Severity is M and Detection is L, THEN Risk is VL.

Table 3
Features of the linguistic variables.

Linguistic term	Probability of occurrence	Severity	Detection
Remote	It would be very unlikely for these failures to be observed even once	A failure that has no effect on the system performance	Detection of the failure cause is practically certain
Low	Likely to occur once, but unlikely to occur more frequently	A failure that would cause slight annoyance to the operator, but that cause no deterioration to the system	Detection of the failure cause is much likely to be detected
Moderate	Likely to occur more than once	A failure that would cause a high degree of operator dissatisfaction or that causes noticeable but slight deterioration in the system performance	Likely to be detected
High	Near certain to occur at least once	Causes significant deterioration in the system performance	Hardly detected, unless testing is performed
Very high	Near certain to occur several times	A failure that cause seriously affect the system performance	The failure cause can be detected by testing only

10. IF Occurrence is M and Severity is L and Detection is R, THEN Risk is VL.
11. IF Occurrence is M and Severity is H and Detection is H, THEN Risk is H.
12. IF Occurrence is M and Severity is L and Detection is L, THEN Risk is L.
13. IF Occurrence is L and Severity is L and Detection is L, THEN Risk is VL.
14. IF Occurrence is L and Severity is M and Detection is L, THEN Risk is L.
15. IF Occurrence is L and Severity is M and Detection is L, THEN Risk is L.
16. IF Occurrence is L and Severity is L and Detection is H, THEN Risk is L.
17. IF Occurrence is M and Severity is L and Detection is L, THEN Risk is VL.
18. IF Occurrence is H and Severity is M Detection is M, THEN Risk is H.
19. IF Occurrence is M and Severity is L and Detection is M, THEN Risk is L.
20. IF Occurrence is H and Severity is H and Detection is M, THEN Risk is H.
21. IF Occurrence is M and Severity is M and Detection is M, THEN Risk is L.
22. IF Occurrence is L and Severity is L and Detection is R, THEN Risk is VL.
23. IF Occurrence is M and Severity is M and Detection is L, THEN Risk is L.
24. IF Occurrence is R and Severity is M and Detection is L, THEN Risk is VL.

The fuzzy RPNs or fuzzy risk results are obtained by the defuzzification using the same data from the traditional FMEA, and expressing the three variables considered linguistically with aid of the membership function and the fuzzy rule base. From experts' knowledge, if the fuzzy RPN value is 5 and more than 5 then it will be considered as one of the most critical parameters. In this study, centroid method is used for defuzzification. The values of conventional RPN and fuzzy RPN for sugar mill boiler are shown in Tables 2 and 4. From Table 2, the most critical parameters identified by conventional FMEA for boiler are fuel type, fuel moisture, drum speed, air flow, motor load, silo level, furnace temperature, oil pressure and hydraulic drive speed. Most of the articles indicated that the conventional FMEA has some limitations [10,26,27]. One of the major disadvantages of the traditional FMEA is allocation of equal weight to each indicator of the RPN. In order to overcome this limitation, fuzzy FMEA has been carried out to the same systems. From Table 4, it has been observed that the most significant parameters identified by fuzzy FMEA for sugar mill boiler are the same and, furthermore, the RPN values are in good agreement with each other. The parameters indicated by an asterisk (*) are considered as critical parameters. Once the RPN values are determined, subsequently corrective action must be taken, on the above mentioned selected parameters in order to minimize the failures. In this paper, the process parameters selected by FMEA and fuzzy FMEA are optimized by Taguchi method and genetic algorithm.

3. Results and discussion

3.1. Taguchi method

Taguchi method is one of the most powerful quality tools that can be applied to improve the quality of the product or the process parameter design. It is an efficient and systematic approach to reduce the experiment trials as compared to traditional experimental design methods, which require large number of experiments [28,29]. In this method, high quality is achieved by optimizing product or process parameters without increasing the cost [30]. The significant process parameters and their levels are selected on the basis of conducting the preliminary experiments. In this research work, four control factors and three levels are chosen for analyzing the boiler component failures. The process parameters with their ranges and levels of drum feeder, screw conveyor and grate are shown in Table 5. Two important tools used in Taguchi method are the orthogonal array (OA) and the signal to noise ratio (S/N ratio). OA is used to minimize the number of experiments, by which quality characteristics are examined. The orthogonal array is selected based on the number of degrees of freedom, which is determined from the number of factors, number of selected interactions, and the number of levels of each factor. Signal to noise ratio (S/N ratio) is employed to analyze the quality characteristics of the product or the process parameters. It is also called as statistical measure of performance and is used as an objective function for optimizing parameters. It is the ratio of the mean (signal) to the standard deviation (noise). In this research work, L9 OA and "smaller is better" S/N ratio are employed.

The process parameters at different levels are assigned in the selected orthogonal array. It has nine trials. The plant was run three times for the same set of parameters given in L9 OA. The observations were made for every 1 h and the number of failures, which occurred during that time, were noted and the percentage of failures was calculated. Since the failures are the smaller is the better type of quality characteristics, smaller is the better S/N ratio were computed for each of the 9 trials and the values were recorded. The average values of the failure and S/N ratios for each parameter at different levels are computed. From this, minimum failure and maximum S/N ratio for each factor is selected as the best values for getting minimum failures of the boiler components. For example, from Table 6, it is clear that the failures of the screw conveyor are minimum at the first level of parameter E ($E1$ – bagasse), the first level of parameter F ($F1$ – 49%), the first level of parameter G ($G1$ – 600 rpm) and the third level of parameter H ($H3$ – 120 T/h). The S/N ratio is also maximum at the same levels of the parameters ($E1$,

Table 4
Comparison between conventional RPN and fuzzy RPN for boiler.

Potential failure modes (process defects)	Potential causes of failures	Conventional RPN	Ranking	Fuzzy RPN	Ranking
Screw conveyor failure	*Fuel type	252	9	7	12
	Size of fuel	60	15	3.5	13
	Foreign material	18	33	1.3	26
	*Fuel moisture	336	6	7.92	4
	Improper maintenance of eddy current	24	31	1.51	22
	Gears not properly connected in the drum	36	26	1.27	29
	*Drum speed	384	3	7.8	6
	Motor damaged	48	18	2.5	15
	*Air flow	392	1	8.38	2
	Improper maintenance	16	34	1.29	28
	Mal function	32	28	2.36	16
	Fatigue	8	38	0.383	37
Drum failure	*Fuel type	294	7	7.42	9
	Size of fuel	45	20	1.3	27
	Foreign material	27	30	0.36	38
	*Fuel moisture	392	1	8.5	1
	Improper maintenance	36	26	2.13	17
	Mal function	40	25	1.91	20
	Fatigue	8	38	0.438	35
	*Fuel level (silo level)	343	5	8.13	3
	Door not properly closed	54	17	2.13	18
	*Motor load (current)	384	3	7.48	8
	Relay contact	42	24	1.4	23
	Rotation improper	16	34	0.87	34
	Oil level in gear box	45	20	0.95	32
Grate failure	*Furnace-temperature	252	9	7.54	7
	Fuel heap	30	29	1.34	27
	Air flow	24	31	1.23	30
	*Fuel type	288	8	7.3	10
	Size of fuel	12	37	0.42	36
	Foreign material	48	18	1.35	24
	Fuel moisture	72	13	2.95	14
	*Hydraulic drive-speed	240	12	7.85	5
	*Oil pressure	245	11	7.14	11
	Oil seal damaged	45	20	0.95	33
	Oil level	64	14	1.97	19
	Improper lubrication	6	40	0.32	40
	Improper maintenance	45	20	1.05	31
	Mal function	60	15	1.86	21

Table 5
Process parameters with their ranges and values at three levels for boiler components.

Name of the component	Process parameters	Range	Level 1	Level 2	Level 3
Screw conveyor	*E* – fuel type	3 types	B	B + C	B + C + PB
	F – fuel moisture in %	49–51	49	50	51
	G – drum speed in rpm	600–800	600	700	800
	H – air flow in T/h	100–120	100	110	120
Drum feeder	*P* – fuel type	3 types	B	B + C	B + C + PB
	Q – fuel moisture in %	49–51	49	50	51
	R – motor load in ampere	11.5–40	11.5	25	40
	S – silo level in %	50–100	50	75	100
Grate	*K* – furnace temperature (°C)	800–1400	800	1200	1400
	L – oil pressure (kg/cm^2)	20–60	20	40	60
	M – hydraulic drive speed (rpm)	2–4	2	3	4
	N – fuel type	3 types	B	B + C	B + C + PB

B, bagasse; C, cane trash; PB, palm boom.

*F*1, *G*1, *H*3) as the best values for getting minimum failures of the screw of conveyor.

Once the experiment has been conducted, the analysis of variance (ANOVA) was carried out using the results of the experiments to study the significance of the individual parameters on the performance of the boiler components. For example, the parameter "fuel type" significantly affects both mean and variation in the drum feeder and grate failures [31,32]. However, the results obtained so far are not sufficient enough to find the optimum parameters in order to minimize failures. Hence, some more information is required to conclude with an optimum parameter set. The interpretation methods, percent contribution, estimating the mean, confidence interval around the estimated mean are required to validate the results so far obtained. Confirmation experiments were conducted at the optimum setting of the process parameters and the result was compared with confidence interval around the estimated mean.

The optimization of process parameters of drum feeder and grate by Taguchi method has been already reported by Maria Jaya Prakash and Senthivelan [31,32]. In the same manner, the process parameters of screw conveyor have been optimized. The optimum level and value of process parameters and the results of

Table 6
Average values of screw conveyor, drum feeder and grate failures and S/N ratios at different levels.

Name of the component	Factors	Level 1		Level 2		Level 3	
		Screw conveyor failure	S/N ratio	Screw conveyor failure	S/N ratio	Screw conveyor failure	S/N ratio
Screw conveyor	Fuel type (E)	2.06	−6.53	4.12	−12.28	4.93	−13.93
	Fuel moisture (F) (%)	3.23	−9.65	3.94	−11.69	3.94	−11.39
	Drum speed (G) (rpm)	3.49	−10.28	3.67	−11.01	3.94	−11.45
	Air flow (H) (T/h)	3.94	−11.10	3.85	−11.49	3.32	−10.15
Drum feeder	Fuel type (P)	2.71	−8.63	4.20	−12.40	4.20	−12.46
	Fuel moisture (Q) (%)	3.33	−10.24	4.13	−12.16	3.66	−11.09
	Motor load (R) (A)	3.37	−10.32	3.83	−11.61	3.90	−11.57
	Silo level (S) (%)	3.98	−11.52	3.58	−11.07	3.55	−10.89
Grate	Furnace temperature (K) (°C)	3.35	−11.13	3.77	−12.36	3.98	−11.72
	Oil pressure (L) (kg/cm^2)	3.35	−11.72	3.14	−11.13	4.61	−12.36
	Hydraulic drive speed (M) (rpm)	4.19	−12.60	2.94	−11.12	3.98	−11.72
	Fuel type (N)	2.72	−9.10	4.82	−13.50	3.56	−11.25

confirmation experiments for drum feeder, screw conveyor and grate are shown in Table 6. Though the failures occurring during the cogeneration process have been reasonably minimized by using Taguchi method, in order to achieve failures – free system during the processes, genetic algorithm technique is applied as well on the optimized parameters obtained by Taguchi method [33].

3.2. Genetic algorithm

A genetic algorithm is a well-known method to optimize an objective function with linear or non-linear constraints. It is a stochastic global search technique, in which, the derivative evaluation of the error function is not required. It is recognized to be highly efficient in dealing with large, discrete, non-linear and poorly understood optimization problems [34,35]. Despite classical optimization techniques such as mathematical and heuristic approaches, genetic algorithms have become sequencing, transportation, and many others. Genetic algorithms (GAs) are stochastic search techniques based upon the mechanism of natural selection and population genetics. A clear advantage of using GA over other methods is potential to locate global optimum or near global optimum solution without a necessity to search for all solution spaces. Moreover, the processing time only increased as the square of the project size and not exponentially [36].

Recently, GA is becoming popular to the optimization problems in different fields of application mainly because of its robustness in finding optimal solution close to global minimum [37]. Genetic algorithms operate on a population of potential solutions applying the principle of “survival of the fittest” to produce increasingly better approximations to a solution. At each generation, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain, and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of better suited populations [38].

In GA a candidate solution represented by a sequence of genes is called chromosome. The potential of chromosome is called its fitness function, which is evaluated by the objective function. A set of selected chromosomes is called population and the population is subjected to generations (number of iterations). In each generation, new population is generated through genetic operations such as selection, crossover and mutation [39,40]. Highly fit individuals are given opportunities to reproduce by exchanging pieces of their genetic information, in a crossover procedure, with other highly fit individuals. This produces new ‘offspring’ solutions, which share some good characteristics taken from both parents. Mutation is applied after crossover by altering some genes in the strings. The offspring can either replace the whole population or replace less fit individuals. This evaluation and selection–reproduction cycle is

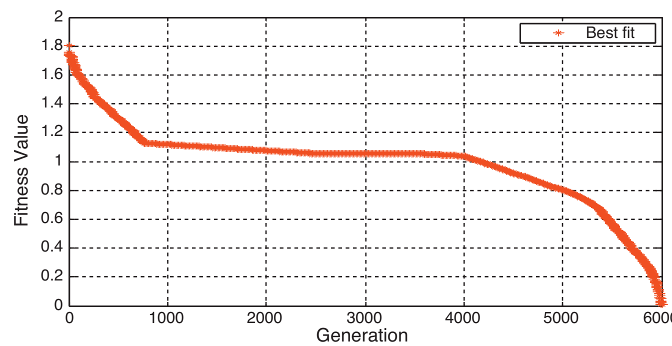

Fig. 4. Evaluation of generations for drum feeder optimization.

repeated until a satisfactory solution is found [41]. Further, Vedat Savas et al. [42] outlined the unique characteristics of GA while optimizing the surface roughness in the process of tangential turn milling. GA moves through the solution space starting from a population of points and not from a single point. This is similar to the calculus based methods where we have to restart the solution from number of points to ensure global convergence. GAs work with the objective function information directly and not with any other auxiliary information like derivatives. Constraints are included in the objective function using some penalty function. GAs use probabilistic rules and not deterministic rules.

In drum feeder optimization work, the process parameters fuel type, fuel moisture, motor load, and silo level are considered as basic elements of GA. A mathematical model has been developed by using Taguchi’s orthogonal array and MINITAB. The model has been used as objective function in the genetic algorithm [15]. The objective function and constraints of the drum feeder are defined as follows:

$$Y = -5.77 + 0.741P + 0.163Q + 0.0188R - 0.00867S \qquad (1)$$

Minimize: $Y(P, Q, R, S)$
Constraints
Bounds on fuel type: $1 \le P \le 3$
Bounds on fuel moisture (%): $48 \le Q \le 52$
Bounds on motor load (A): $9 \le R \le 14$
Bounds on silo level (%): $90 \le S \le 100$

The problem of genetic algorithm has been solved using MATLAB. The parameters used in GA are population size as 100, cross over probability as 0.7, mutation probability as 0.1 and the number of generations as 6000. The evaluation of generations and the best values obtained by GA are shown in Figs. 4 and 5. The best

Table 7
Optimization results obtained by Taguchi method for boiler components.

Name of the component	Process parameters	Optimum level	Optimum Value	Confirmation experiments result
Screw conveyor	E – fuel type	1	B	0.8%
	F – fuel moisture in %	1	49	
	G – drum speed in rpm	1	600	
	H – air flow in T/h	3	120	
Drum feeder	P – fuel type	1	B	0.65%
	Q – fuel moisture in %	1	49	
	R – motor load in ampere	1	11.5	
	S – silo level in %	3	100	
Grate	K – furnace temperature (°C)	1	800	0.9%
	L – oil pressure (kg/cm^2)	2	40	
	M – hydraulic drive speed (rpm)	2	3	
	N – fuel type	1	B	

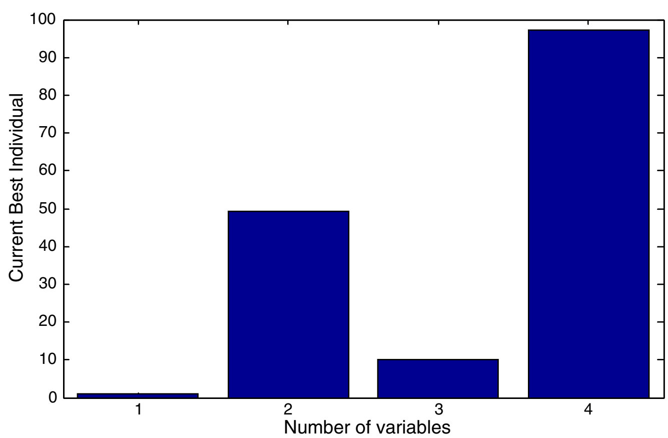

Fig. 5. Best individual values obtained by GA for drum feeder optimization.

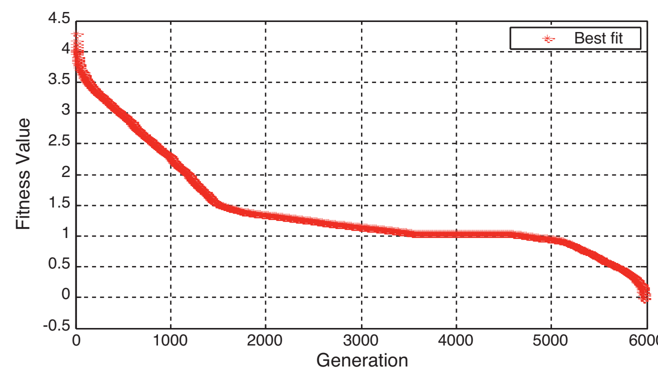

Fig. 6. Evaluation of generations for screw conveyor optimization.

values obtained by using GA are noted in Table 7 and the confirmation experiments have been conducted using these parameters. The percentage of drum failures occurring during the confirmation experiments is shown in Table 7.

In the same manner, the process parameters of screw conveyor and grate are optimized by using genetic algorithm. In screw conveyor optimization work, the process parameters drum speed, air flow, fuel moisture and fuel type are considered as basic elements of GA. The objective function and constraints of the screw conveyor are defined as follows:

$$Y = -15.2 + 1.43E + 0.358F + 0.00224G - 0.0314H \tag{2}$$

Minimize: $Y(E, F, G, H)$
Constraints
Bounds on fuel type: $1 \le E \le 3$
Bounds on fuel moisture (%): $48 \le F \le 52$
Bounds on drum speed (rpm): $550 \le G \le 650$
Bounds on air flow (T/h): $110 \le H \le 125$

The evaluation of generations and the best values obtained by GA are shown in Figs. 6 and 7. The best values obtained by using GA are noted in Table 8 and the confirmation experiments have been conducted using these parameters. The percentage of screw conveyor failures occurring during the confirmation experiments is shown in Table 8.

In grate optimization work, the process parameters furnace temperature, oil pressure, hydraulic speed, and fuel type are considered as basic elements of GA. The objective function and constraints of the grate are defined as follows:

$$Y = 0.74 + 0.00105K + 0.0314L - 0.106M + 0.419N \tag{3}$$

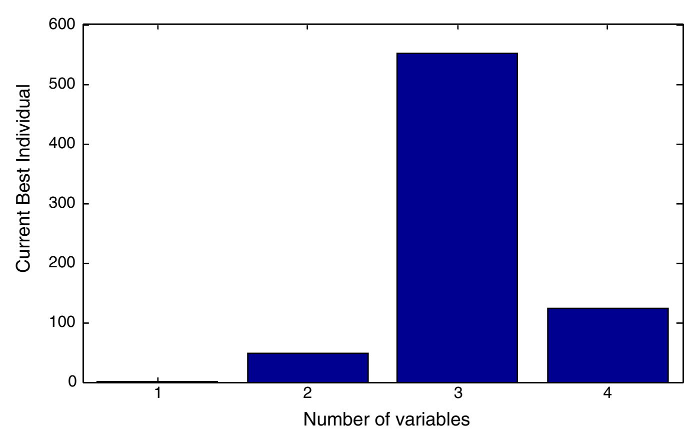

Fig. 7. Best individual values obtained by GA for screw conveyor optimization.

Minimize: $Y(K, L, M, N)$
Constraints
Bounds on furnace temperature (°C): $750 \le K \le 850$
Bounds on oil pressure (kg/cm^2): $35 \le L \le 45$
Bounds on hydraulic speed (rpm): $1 \le M \le 5$
Bounds on fuel type: $1 \le N \le 3$

The evaluation of generations and the best values obtained by GA are shown in Figs. 8 and 9. The best values obtained by using GA are noted in Table 9 and the confirmation experiments have been conducted using these parameters. The percentage of failures occurring during the confirmation experiments is shown in Table 9.

The results obtained by Taguchi method and GA for screw conveyor, drum feeder and grate are shown in Table 11.

Table 8
Optimization results obtained by GA for drum feeder.

	Fuel type	Fuel moisture (%)	Motor load (A)	Silo level (%)	Percentage of failures
Genetic algorithm	B	48.5	10.00	98	0.002

Table 9
Optimization results obtained by GA for screw conveyor.

	Fuel type	Fuel moisture (%)	Drum speed (rpm)	Air flow (T/h)	Percentage of failures
Genetic algorithm	B	48.5	560	123	0.001

Table 10
Optimization results obtained by and GA for grate.

	Furnace temperature (°C)	Oil pressure (kg/m^2)	Hydraulic drive speed (A)	Fuel type	Percentage of failures
Genetic algorithm	753	42	3	B	0.004

Table 11
Comparison of results obtained by Taguchi method and GA for sugar mill boiler.

Sl. No.	Name of the components	Percentage of defects (Taguchi method)	Percentage of defects (genetic algorithm)
1	Screw conveyor	0.8	0.001
2	Drum feeder	0.65	0.002
3	Grate	0.9	0.004

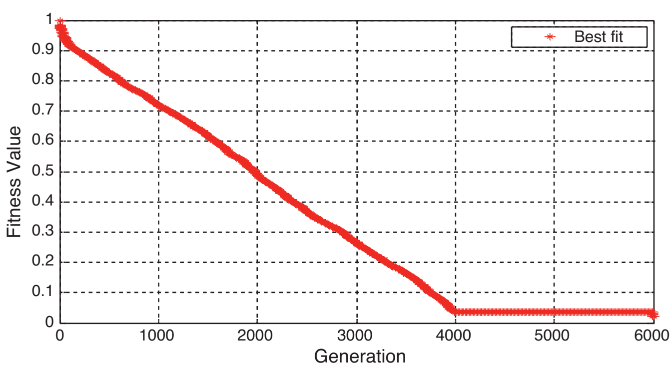

Fig. 8. Evaluation of generations for grate optimization.

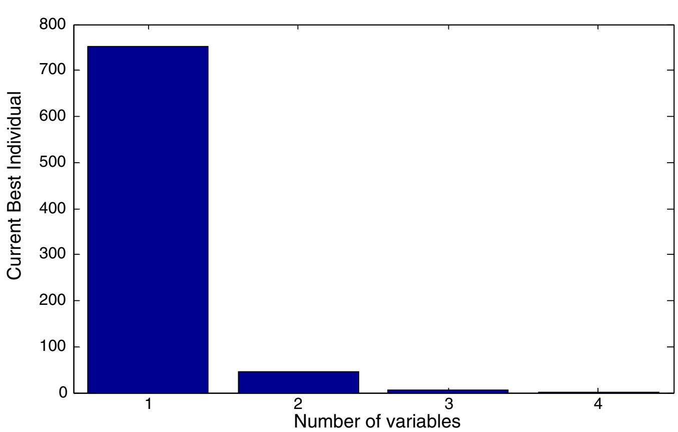

Fig. 9. Best individual values obtained by GA for grate optimization.

4. Conclusions

Considering the case of the boiler, the process parameters which affect the quality of screw conveyor, drum feeder and grate have been identified and selected by using FMEA. Since the conventional FMEA has some limitations, fuzzy logic is applied into the conventional FMEA. It is clear from Table 4 that the most critical parameters selected by conventional FMEA and fuzzy FMEA are the same, though the rankings differ. Taguchi method has been applied to optimize the process parameters selected by conventional FMEA and fuzzy FMEA. The optimized process parameters, levels, values and the confirmation experiments results have been shown in Table 6, and, it can be observed that the failures of screw conveyor, drum feeder and grate are reasonably minimized. Furthermore, genetic algorithm technique has been applied on the optimized parameters obtained by Taguchi method. The results obtained by GA for screw conveyor, drum feeder and grate have been shown in Tables 7–9. The comparison of results obtained by Taguchi method and GA has been shown in Table 10. The percentage of defects has been significantly reduced after the application of GA technique. From the present study, the following inferences have been arrived at:

1. The most significant parameters identified by conventional FMEA and fuzzy FMEA for boiler components failures are drum speed, air flow, fuel moisture and fuel type for screw conveyor; fuel type, fuel moisture, motor load and silo level for drum feeder; and furnace temperature, oil pressure, hydraulic drive speed and fuel type for grate.
2. The best levels and values of process parameters obtained by Taguchi method are *E*1 (bagasse), *F*1 (49%), *G*1 (600 rpm), *H*3 (120 T/h) for screw conveyor; *P*1 (bagasse), *Q*1 (49%), *R*1 (11.5 A), *S*3 (100%) for drum feeder; and *K*1 (800 °C), *L*2 (40 kg/cm^2), *M*2 (3 rpm), *N*1 (bagasse) for grate (Table 6).
3. The confirmation experiments results obtained by Taguchi method for screw conveyor, drum feeder, and grate are 0.65%, 0.8% and 0.9% respectively.
4. The genetic algorithm technique has been applied on the optimized parameters obtained by Taguchi method. A mathematical model has been developed for screw conveyor, drum feeder and grate and it has been used as the objective function in the GA.
5. After applying the genetic algorithm technique on the optimized parameters obtained by Taguchi method, the percentage of screw conveyor failure, drum feeder failure and grate failure are drastically reduced to 0.001, 0.002 and 0.004 respectively.

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